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Assessment of regional threats to human water security adopting the global framework: A case study in South Korea

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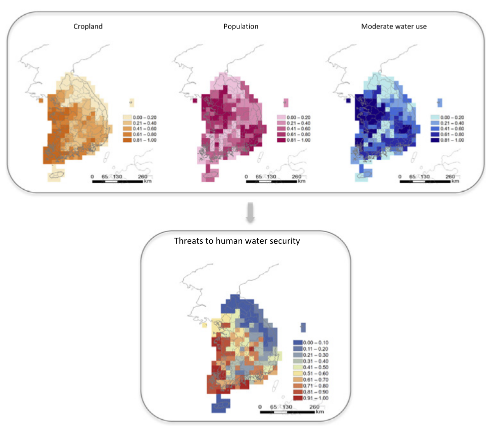
HIGHLIGHTS

- Strong correlations were found between global and regional indicators except for investment benefits.
- Three key indicators represent the majority of the spatial variation in incident threat.
- R25° is the most appropriate spatial resolution for regional analysis.

GRAPHICAL ABSTRACT



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ABSTRACT

Water resources have been threatened by climate change, increasing population, land cover changes in watersheds, urban expansion, and intensive use of freshwater resources. Thus, it is critical to understand the sustainability and security of water resources. This study aims to understand how we can adequately and efficiently quantify water use sustainability at both regional and global scales with an indicator-based approach. A case study of South Korea was examined with the framework widely used to quantify global human water threats. We estimated the human water threat with both global and local datasets, showing that the water security index using global data was adequately correlated with the index for regional data. However, particularly poor associations were found in the investment benefit factors. Furthermore, we examined several different aspects of the index with the local datasets as they have relatively high spatial and temporal resolution. For example, we used cropland percentage, population and moderate water use as surrogate indicators instead of employing the approximately 20 original indicators, and we presented a regression model that was able to capture the spatial variations from the original threat index to some extent. This finding implies that it would be possible to predict water security or sustainability using existing indicator datasets for future periods, although it would require regionally developed relationships between water security and such indicators.

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1. Introduction

Water resources have been threatened by increasing population, land cover changes in watersheds, urban expansion, and intensive use of freshwater resources. Additionally, climate change due to carbon emissions from human activities is causing additional threats to water resources (Hoff, 2009; Vörösmarty et al., 2010). Given the unsustainability of the global water system, water resource management is required to promote the coordinated development and management of water, land and related resources to maximize the resultant economic and social welfare in an equitable manner without compromising the sustainability of vital ecosystems (Loukas et al., 2007).

Water resource management incorporates technical, political, legislative, and organizational components within a river basin (Loukas et al., 2007). An indicator-based approach using representative indicators is often used to illustrate such complex phenomena. This approach is particularly useful because the spatial distributions and temporal changes of major indicators can provide direction for policies related to sustainable water use. In the early stages of conceptualizing the quantitative assessment of water use sustainability, basic indicators primarily focused on issues of human water requirements and vulnerability while using fewer datasets based on the limited data available. Furthermore, many aspects of water use, supply and scarcity are equally important, making the act of selecting the criteria with which to assess water as much a policy decision as a scientific one (Brown and Matlock, 2011).

The most widely used indicator is the Falkenmark indicator (Falkenmark, 1989), which is defined as the fraction of the total annual runoff available for human use with surveying or calculating the water usage per person. Based on per capita usage, the water conditions in an area can be categorized as having no stress, stress, scarcity, or absolute scarcity. Here, the thresholds for areas with water stress and scarcity are 1700 m^3 and 1000 m^3 per capita per year, respectively. Additionally, Vörösmarty et al. (2000) constructed an indicator for 'water usage per water supply'. Future water demand was estimated using the predicted population change and current water usage, which includes domestic, industrial, irrigation, and agricultural water consumption. The water supply was defined as the annual mean surface water and shallow aquifer runoff (Postel et al., 1996), and the future water supply was estimated through changes in the water supply due to climate change.

Anthropogenic water usage has been included in recent studies to estimate the future sustainability of water availability (e.g., Döll et al., 2003; Milly et al., 2005; Sun et al., 2008; Koutroulis et al., 2018). Milly et al. (2005) considered the runoff per area of the watershed as the total runoff, used the largest portion of human water use as the consumption, and calculated the global water availability using future climate change scenarios. In addition, Sun et al. (2008) diversified and subdivided the assessment items to determine the sustainability of future water use. In the southern US, the demand and supply of water resources in the temporal range from the past to 2020 were evaluated, and the water sustainability was assessed using a 'stress index' (Sun et al., 2008). The parameters considered for evaluating the water supply include precipitation, evapotranspiration, groundwater supply, and return flow. Water is needed for commercial, residential, industrial, irrigation, livestock, mining, and thermoelectric uses. The hydrologic unit code (HUC) was selected as the spatial unit to evaluate the stress index in 13 states.

Furthermore, ecosystems have begun to be addressed along with demand and supply in the concept of water management. In addition to human water security, ecological health and biodiversity are also related to water use worldwide (Vörösmarty et al., 2010). However, human water security issues have been considered more important than water security issues in natural systems as part of policy making processes, such as decision making for dam construction. As a result, ecological characteristics, such as biodiversity in the aquatic environment, have markedly degraded due to intensive development and investment in water use infrastructure, such as dams (Vörösmarty et al., 2010).

The abovementioned global studies of water use sustainability or water security are widely adopted in regional studies (e.g. Host et al., 2011; Sheldon et al., 2012; Zeng et al., 2013; Hutchins et al., 2018; Vollmer et al., 2018). All of these studies develop their own indicators according to their purposes. For example, Sheldon et al. (2012) has developed the indicators for assessing the river ecosystem heath in Southeast Queensland, Australia. Also the impacts of future land-use and climate stressors on water resources quality has been evaluated with the indicators approaches in the upper Thames river basin, United Kingdom (Hutchins et al., 2018). However, these studies are often limited in evaluating the robustness of such indicators and indices.

Thus, this study aims to understand the robustness of global indicator-based studies applied to regional scales to quantify sustainable water use through the example of adjusted human water security from Vörösmarty et al. (2010). Our specific objectives are twofold: 1) we assess the credibility of global data by evaluating the global water indicators and indices compared to local data in South Korea, and 2) we focus on the future predictability of an index by examining it using the limited amount of data that is routinely available for most regions.

2. Data and methods

2.1. Study domain: South Korea

In this study, human water security is assessed for South Korea (Fig. 1), covering an area of 48,877 km^2 with a population of almost 50 million people. The Korean government developed the Hydrologic Unit Map, which divides the river basins for managing the rivers and water in South Korea. The Hydrologic Unit Map is classified into 21 large basins (black line in Fig. 1), 117 medium-size sub-basins (gray line in Fig. 1) and 850 small standard basins (http://wamis.go.kr). Korea provides data with relatively high quality and resolution and thus offers an opportunity to evaluate and adopt the global water security indicators.

2.2. Global and regional threat index assessment

Vörösmarty et al. (2010) utilized an indicator-based approach to quantify human water security. As shown in the schematic diagram (Fig. 2), their study identified 23 geospatial stressors (i.e., indicators) organized under the 4 themes of catchment disturbance, pollution, water resource development and biotic factors. The incidental human water security threats, i.e., incident threat (IT), were further adjusted using investment benefit factors (IBFs) comprised of five drivers reflecting technological investments that can improve human water security. The indicators for each theme were aggregated by their relative weights based on expert assessment and were then further aggregated into incident human water threats and adjusted human water threats, i.e., adjusted threat (AT) (Table 1).

Vörösmarty et al. (2010) collected global data for the stressors and IBFs (engineered systems) for times concurrent with the reference year of 2000 (hereafter referred to as V2000) using data ranging from 1974 to 2006. The data were interpolated to a resolution of 0.5° on a latitude and longitude grid. This study used the subset of those datasets for the domain of South Korea.

This study collected the regional data over South Korea with reference years of 2000 and 2010 (hereafter referred to as K2000 and K2010, respectively) from various sources (refer to supplement A). The raw data that were collected at different spatial resolutions, such as at the sub-basin scale, were spatially interpolated to multiple spatial resolutions of 0.5°, 0.25° and 0.1°.

Fig. 1. Study domain of South Korea. The thick and thin lines represent the basins and sub-basins, respectively, according to the Hydrologic Unit Map of Korea.

All collected indicator data were standardized using the normalization process, in which the raw values of each indicator were transformed into the values of the cumulative distribution function (CDF), i.e., CDF normalization. Then, the normalized stressor indicators were integrated to estimate the indices of the 4 themes (Eq. (1)) and the IT index from the weighted values.

$$IT_i = \sum_{j=1}^{4} \sum_{k=1}^{d_j} W_j \omega_{k,j} D_{i,j,k} \tag{1}$$

where IT_i is the IT index for grid cell i, W_j is the weight of theme j, $\omega_{k,j}$ is the weight of indicator k within theme j, d_j is the number of indicators within theme j, and $D_{i,\,j,\,k}$ is the standardized score of indicator k within theme j for grid cell i. Both W_j and $\omega_{k,j}$ sum to 1.0, where $j = 1, 2, \ldots 4$ and $k = 1, 2, \ldots d_j$. Note that the original weights were determined from expert surveys and were rescaled in this study to derive the adjusted weights according to the data availability of the regional datasets (Table 1).

Similar to (1), the IBF drivers were integrated into the IBF index. Finally, the IBF index was used to scale the IT index to the AT index (Eq. (2)), which was rescaled to a 0–1 scale using CDF standardization.

$$AT_i = IT_i \cdot [1 - IBF_i] \tag{2}$$

where AT_i and IBF_i are AT and IBF indices for grid cell i.

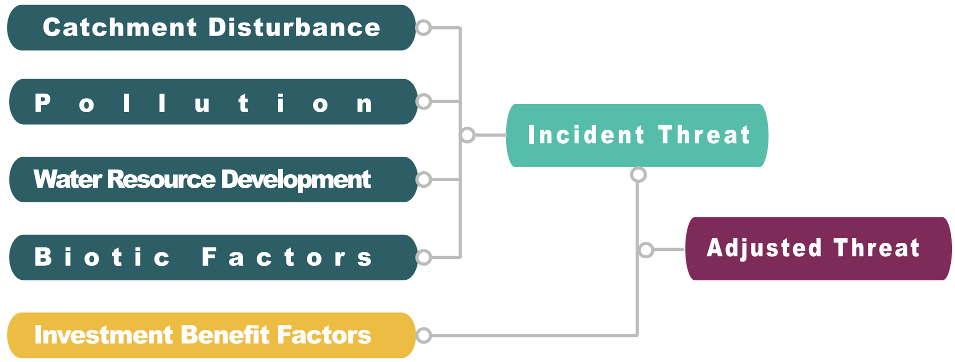

Fig. 2. Conceptual framework for human water security threat (Vörösmarty et al., 2010).

2.3. Regression model for the threat index

To simplify the index calculation based on regional data availability, we constructed regression models to calculate the AT using a limited number of key indicators instead of the original indicators. Here, we selected the key indicators based on a quantitative approach, i.e., principal component analysis (PCA), and a qualitative approach, i.e., expert judgment. The selected indicators were linearly regressed to estimate AT, as shown below.

$$\widehat{AT_i} = \beta_0 + \sum_{l=1}^{4} \beta_l S_{i,l} \tag{3}$$

where β_x are the coefficients for the linear regression; $S_{i,l}$ is the score of the selected indicator l, where $l = 1, 2, \ldots L$, for grid cell i; and L is the number of selected indicators.

PCA considers the variations in the data and highlights the trends in the dataset to simplify the interpretation by extracting important information called principal components (PCs) when there are too many variables associated with a sample set (Abdi and Williams, 2010). Therefore, PCA is particularly useful when multiple sets of associated data or observations are available. For example, there are many parameters that contribute to water availability, including evapotranspiration, precipitation, river network, land use, water resource management, and groundwater supply. PCA could determine whether it is possible to form a smaller number of uncorrelated variables to simplify the analysis and interpretation. River network and precipitation could form one variable known as surface water; groundwater supply and evapotranspiration could form one groundwater variable; and land use and water resource management could form a policy influence variable.

3. Threat indices with the regional dataset

3.1. Incident and adjusted threats to human water security in Korea

The indicators were integrated with the weights (Table 1) to the 5 index themes. The first four themes were aggregated into the IT index,

Table 1
Indicator data availability and their weights for the regional study in Korea.

Division	Theme	Symbol	Driver	Data availability	Rescaled weights	
					Original	Rescaled
Human water security threat	Catchment disturbance	S1	Cropland	Y	0.38	0.38
		S2	Impervious surfaces	Y	0.28	0.28
		S3	Livestock density	Y	0.20	0.20
		S4	Wetland disconnectivity	Y	0.14	0.14
	Pollution	S5	Soil salinization	N	0.13	–
		S6	Nitrogen loading	Y	0.14	0.21
		S7	Phosphorus loading	Y	0.13	0.19
		S8	Mercury deposition	N	0.13	–
		S9	Pesticide loading	Y	0.15	0.22
		S10	Sediment loading	Y	0.07	0.10
		S11	Organic loading	Y	0.18	0.27
		S12	Potential acidification	N	0.05	–
		S13	Thermal alteration	N	0.02	–
	Water resource development	S14	Dam density	Y	0.09	0.09
		S15	River fragmentation	Y	0.03	0.03
		S16	Consumptive water use	Y	0.34	0.34
		S17	Human water stress	Y	0.26	0.26
		S18	Agricultural water stress	Y	0.19	0.19
		S19	Flow disruption	Y	0.09	0.09
	Biotic factors	S20	Non-native fishes (%)	Y	0.13	0.22
		S21	Non-native fishes (#)	N	0.14	–
		S22	Fishing pressure	N	0.27	–
		S23	Aquaculture pressure	Y	0.46	0.78
				Sum	1.00	1.00
Investment benefit factor		B1	Dam density (=S14)	Y	0.16	0.16
		B2	Flow disruption (=S19)	Y	0.17	0.17
		B3	Moderate water use	Y	0.16	0.16
		B4	River corridor access (=S4)	Y	0.06	0.06
		B5	Access to clean drinking water	Y	0.45	0.45
				Sum	1.00	1.00

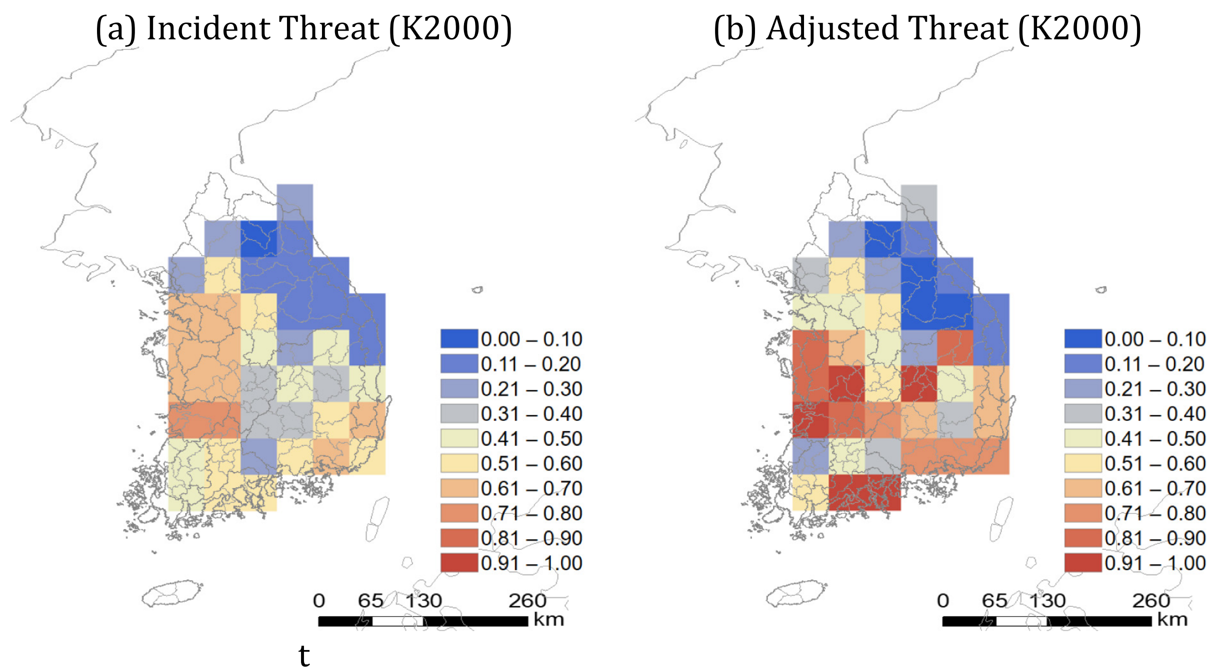

Fig. 3. (a) Incident and (b) adjusted threats from the regional dataset for the year 2000 at a spatial resolution of 0.5°.

which was then integrated with the IBFs to estimate the AT index. The estimated IT and AT in Korea for the reference year, i.e., 2000, at the spatial resolution of 0.5° is the control case for the Korea data (Fig. 3).

For the IT, most of the downstream regions of the major rivers presented high stress, and the upstream regions of the Han River presented low stress. In AT, the downstream region of the Han River basin, where the capital city of South Korea, Seoul, is located, showed relatively low threats compared to other downstream regions. Investigating the detailed indicators for IBFs (not shown) showed that all IBFs except for moderate water use (B3) contributed to reducing the threats. Here, the direct comparison of index values between AT and IT were not suitable since the AT in Eq. (2) was then standardized with CDF normalization.

Table 2
Correlation coefficients among indicators and indices according to the spatial resolution.

	R25 vs. R50	R10 vs. R50
Incident threat	0.88	0.86
Benefit factor	0.75	0.66
Adjusted threat	0.85	0.83

3.2. Effect of spatial resolution

Vörösmarty et al. (2010) evaluated global water threats in 0.5° (≈50 km) grid units. In Korea, the sub-basin units (Fig. 1), in which some of the raw data are available, have an area of approximately 900 km^2, and this grid size is relatively coarse for national evaluation. Therefore, we analyzed the change in the index value according to the change in the resolution to determine the importance of the grid size used at the international level. The raw data were processed using 0.25° (R25), 0.10° (R10), and 0.5° (R50) resolution.

The correlation coefficients of R25-R50 and R10-R50 for IT, IBF, and AT were calculated with K2000 data, and the results are summarized in Table 2. Most of the indices showed high correlations. Both IT and AT showed an average correlation of 0.85 for both resolutions. However, the IBFs showed relatively lower correlations of 0.75 for R25-R50 and 0.66 for R10-R50. This variation is likely due to the difference in

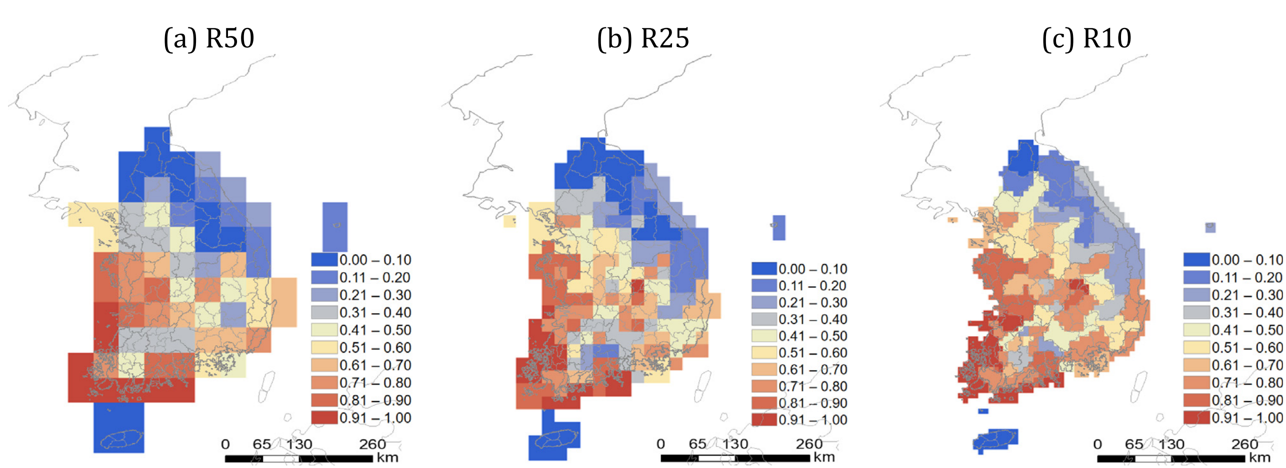

Fig. 4. Adjusted threats from the regional dataset for the year 2000 at spatial resolutions of 0.5, 0.25 and 0.1°.

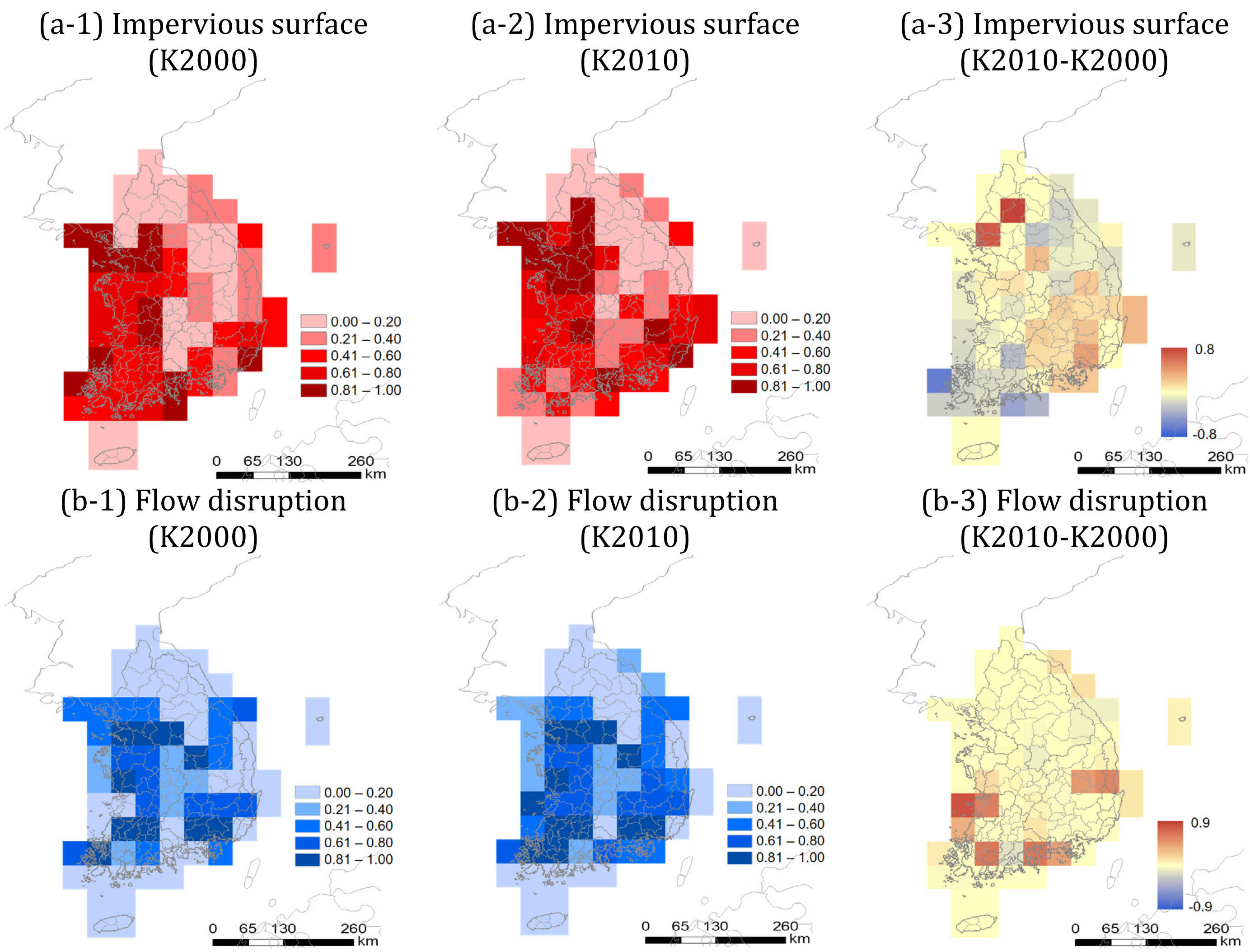

Fig. 5. Selected indicator values of (a) impervious surface and (b) flow disruption for the years 2000 and 2010 and the difference at a spatial resolution of 0.5°.

investment benefits for each region. The IBFs include indicators such as dam density, flow disruption, moderate water use, river corridor access, and access to clean drinking water. R10 and R25 look at each of these indicators at more magnified states than R50 and depict the effects of each indicator on smaller spatial scales. With increased resolution, it is possible to tailor the water resource management needs and investment benefits to a smaller region. Hence, this increase in detail may have played a role in the lower correlation with the R50 data.

Fig. 4 depicts the ATs for R50, R25, and R10. Improvements in the detail of the AT are evident from the R50 to R25 data. As an average sub-

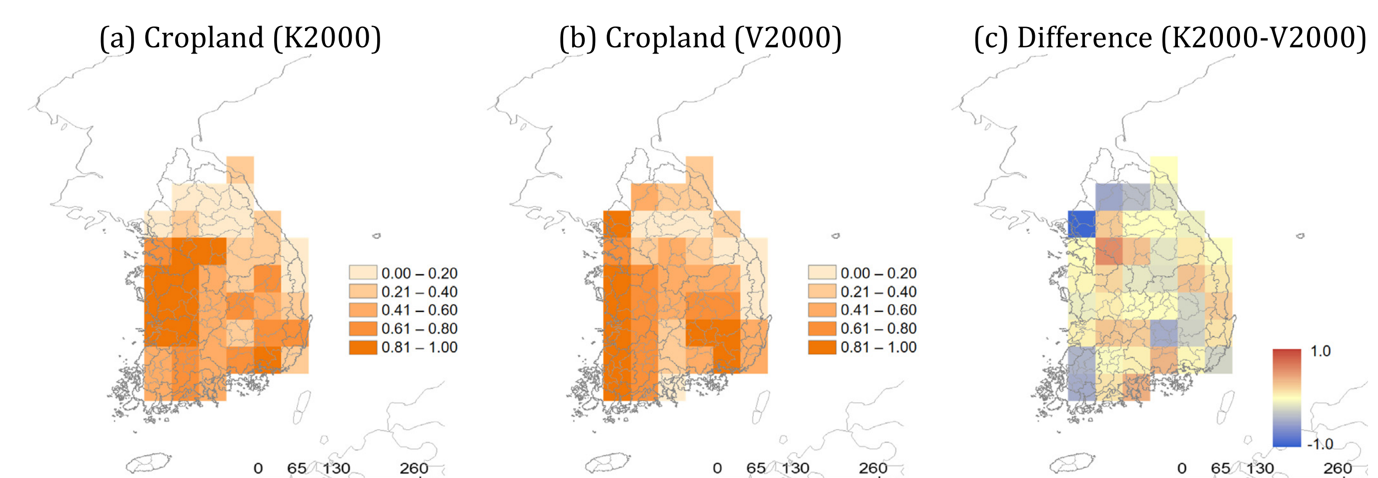

Fig. 6. Selected indicator values of cropland with the values from (a) the regional (Korea) and (b) global datasets and (c) their differences for the years 2000 at a spatial resolution of 0.5°.

Table 3
Comparisons (R and CV of RMSD) between the adjusted threat index and individual indicators based on the reference year of 2000 at a resolution of 0.5°.

Theme		Driver	R	CV of RMSD
Catchment disturbance	S1	Cropland	0.52	0.56
	S2	Impervious surfaces	0.60	0.51
	S3	Livestock density	0.37	0.67
	S4	Wetland disconnectivity	−0.04	1.79
Pollution	S6	Nitrogen loading	0.52	0.55
	S7	Phosphorus loading	0.62	0.49
	S9	Pesticide loading	0.56	0.53
	S10	Sediment loading	0.15	0.73
	S11	Organic loading	0.75	0.40
Water resource development	S14	Dam density	0.49	0.62
	S15	River fragmentation	0.14	0.73
	S16	Consumptive water use	0.64	0.67
	S17	Human water stress	0.66	0.46
	S18	Agricultural water stress	0.36	0.65
	S19	Flow disruption	0.40	0.97
Biotic factor	S20	Non-native fishes (%)	−0.10	2.37
	S23	Aquaculture pressure	0.26	0.69
Investment benefit factor	B1	Dam density	0.49	0.62
	B2	Flow disruption	0.40	0.97
	B3	Moderate water use	0.04	1.37
	B4	River corridor access	−0.04	1.79
	B5	Access to clean drinking water	0.00	0.58

basin is approximately 900 km^2, R50 (~2500 km^2) covers a much larger area and would thus less accurately reflect the AT. R25 (~625 km^2) covers an area much closer to the average, which would increase the AT resolution. The map for R10 shows even greater detail, but the area for R10 (~100 km^2) is much smaller than the average sub-basin; therefore, this degree of resolution is not deemed necessary. In conclusion, R25 is the most appropriate spatial resolution for a regional evaluation of water security threat and resource management.

3.3. Detection of temporal changes in the indicators

Indicators and indices are designed to detect changes in the water threat not only spatially but also temporally. Therefore, we examined the changes in the indicators between K2000 and K2010 in R50 as an example. Fig. 5 shows the maps of impervious surfaces and flow disruption indicators for K2000 and K2010. The comparison also shows K2010-K2000 to highlight the changes for that decade. Development around the capital city of South Korea, Seoul, increased the urban land use. Hence, the impervious surface area has increased in that region. An increase in flow disruption is found southwest of Korea, which is likely due to the addition of dams in that area over the past decade. These variables that exhibit temporal changes would be good indicators to use, particularly when evaluating the performance of environmental plans or actions. These indicators are particularly important because many of the other indicators show spatial variability, not temporal variability.

Table 4
Correlation coefficients among the indices in the global datasets with 25 indicators (V2000_25) and 19 indicators (V2000_19) and the regional datasets (K2000) based on the reference year of 2000 at a resolution of 0.5°.

	V2000_25 vs. K2000		V2000_19 vs. K2000	
	R	CV of RMSD	R	CV of RMSD
Catchment disturbance	1.00	0.00	0.61	0.43
Pollution	0.99	0.25	0.66	0.42
Water resource development	1.00	0.00	0.66	0.45
Biotic factor	0.97	0.20	0.24	0.68
Incident threat	0.99	0.08	0.71	0.35
Investment benefit factor	1.00	0.00	0.16	0.50
Adjusted threat	0.99	0.05	0.34	0.65

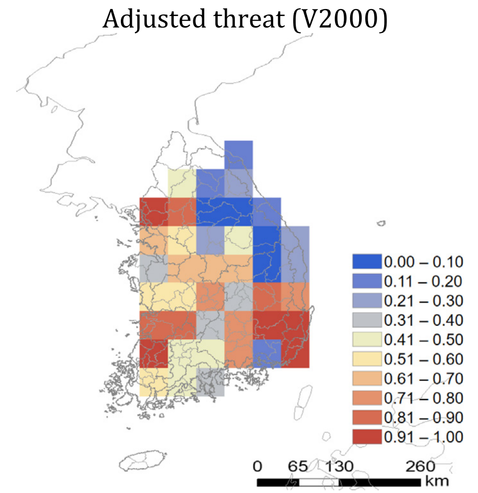

Fig. 7. Adjusted threats from the global dataset for the year 2000 (V2000) at a spatial resolution of 0.5°.

4. Comparison between global and regional datasets

4.1. Individual indicators

The indicator values of the global and regional data over Korea were compared (Fig. 6), and their correlation coefficients (R) and coefficients of variation (CV) with root mean square deviation (RMSD) [CV(RMSD)] were calculated in each grid cell. Table 3 shows that the R values range from 0 to 0.75. The indicators, including organic loading (S11), human water stress (S17), consumptive water use (S16), phosphorous loading (S7) and impervious surfaces (S2), show relatively high R values and small CV(RMSD) values.

The worst indicators with nearly zero R values include access to clean drinking water (B5), wetland connectivity (S4), river corridor access (B4), and moderate water use (B3). The global data for wetland connectivity, which is identical to river corridor access (Table 1), is derived from the Global Lakes and Wetlands Database (GLWD), while the Landsat data at a spatial resolution of 30 m is used for regional data. The global dataset does not generally capture the local disconnectivity in the Seomjin and Youngsan river basins (Fig. 1). In addition, clean drinking water and moderate water use are estimating using the simulated river discharges, which are uncertain in both global and regional datasets.

The global data related to land surface classifications that were derived from MODIS data at a spatial resolution of 10 km were well associated with the regional data that were often derived from Landsat data at a 30 m spatial resolution. This association occurred for indicators such as cropland (S1 in Fig. 6) (refer to the Supplement Table 1). In the theme of pollution sources, the global data for nitrogen loading, phosphorus

Table 5
Percentage of the total variability explained by the principal components based on the 25 indicators in Table 1.

PC #	Explained (%)	Cumulative explained (%)
1	51.29	51.29
2	11.90	63.19
3	9.82	73.01
4	5.34	78.35
5	4.97	83.32
6	4.16	87.48
7	3.21	90.69
8	2.40	93.09
9	2.07	95.16
10	1.51	96.68
12	1.30	97.98
13	1.06	99.04

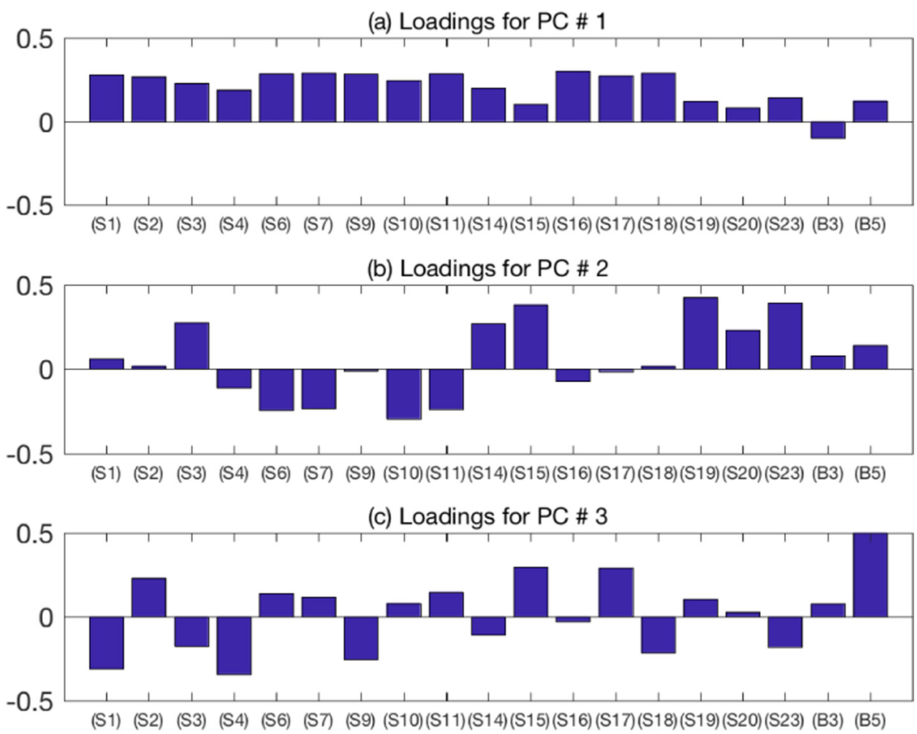

Fig. 8. Percentages of the variance explained by the principal components drawn with the indicators based on the Korean dataset for the year 2010 at a spatial resolution of 0.25°.

loading and organic loading generally showed good association with the regional data estimated based on field surveys. These global datasets are often derived using complicated estimation procedures or simple assumptions based on a variety of global data such as population and land use as human activities are a dominant pollution source (Vörösmarty et al., 2010). Therefore, those global data sources are possibly good, simple proxies for sustainable water use instead of complicated derived global data on pollution loads.

The indicators in the water resource development theme and the IBFs showed relatively low associations between the global and regional data. Water stress indicators were derived from the runoff and additional relevant data, such as population data for human water stress and agricultural land use data for agricultural water stress. As the runoff data were derived from model simulations of both global and regional data, this may represent a source of uncertainty. Further studies that collect ground-based runoff data in Korea are required to confirm this uncertainty.

4.2. Composite indices

The AT index was also estimated with the global data (Table 4 and Fig. 7). Focusing on the impacts of missing indicators in the global data, we found two opposing results (Table 4). In the pollution theme, 4 out of 9 missing indicators did not vary the thematic index with an R value of 0.99 between the 4 and 9 indicator-based indices. This result suggests that those missing indicators did not influence the threat to human water security, at least over Korea, which might be the reason why those indicators were not measured at regional scales over Korea. In contrast to the pollution indicators, 2 out of the 4 missing indicators in the biotic factors theme altered the index value significantly with an R value of 0.59.

Second, the indices with the 17 indicator-based global data were associated with the indices from regional data at varying degrees. As the correlations between the global and regional data were low in the indicators of water resource development, the index-level correlation was

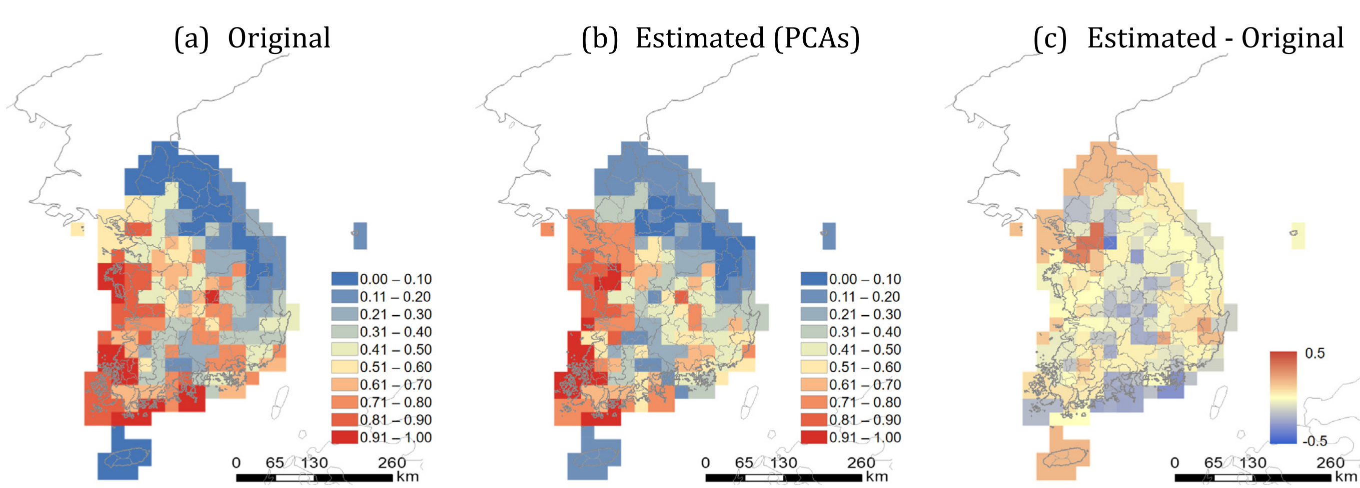

Fig. 9. Adjusted threats with (a) original indicators and (b) three selected indicators based on the PCA and (c) their differences for the year 2010 at a spatial resolution of 0.25°.

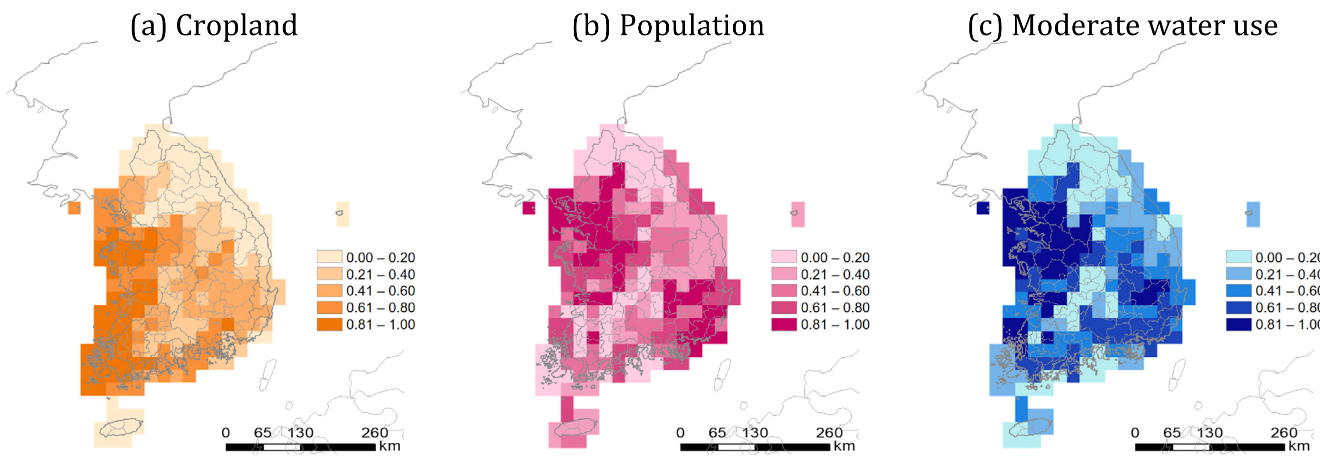

Fig. 10. Three surrogate indicators used to estimate the adjusted threat for water security for the year 2010 at a spatial resolution of 0.25°.

consequently the lowest in the water resource development theme with an R value of 0.34. The R values for the 4 thematic indices ranged from 0.34 to 0.59; their integrated index, i.e., the threat to human water security based on regional data, presented relatively high associations with the index based on the global data with an R value of 0.70 and a CV of 0.12.

5. Simplified index with regional dataset

5.1. PCA-based index

We focus on the possibility of using a limited amount of data to quantify the AT using a PCA-based index (this section) and a surrogate-based index (Section 5.2). In this section, we perform a PCA on the indicator data and select 3 indicators based on the PCA loadings. Then, multiple linear regression models are constructed with those indicators to approximate the AT index.

A PCA transforms a set of observations of possibly correlated variables into a set of linearly uncorrelated variables called PCs. The results show that the first PC explains 51.29% of the variance (Table 5), and the number of indicators shows high loadings for the first PC (Fig. 8). We selected one indicator, the consumptive water loss (S16), that showed the highest loading among the correlated variables for the first PC. Similarly, we selected flow disruption (S19) and access to clean water (B5) as the second and third PCs, respectively.

The three selected indicators were used to construct the multiple linear regression model, estimating the adjusted human water threat index with an R value of 0.90. As shown in Fig. 9a and b, the multiple linear regression model captured the original spatial variability of the low threats in the eastern mountainous regions and high threats in the western coastal regions, while the extreme values in northern and southern Korea were underestimated.

We arbitrarily used the top three PCs; thus, we increased the number of PCs used. The R value of 0.90 that resulted from the three indicators from the three PCs increased slightly to 0.92 when the number of indicators increased to 6. The increased number of key indicators increased the predictability of the AT index, but the increase was negligible when more than three indicators were used.

5.2. Surrogate-based index

While this study focuses on only the present-day index, the multiple regression model with these data could be further extrapolated to a future projection to quantify the adjusted human water security threat. Therefore, a set of surrogate variables were arbitrarily selected and used to approximate the index instead of selecting key indicators according to the PCA results, as described in the previous section (Section 5.1). Crop land, population and water use were selected as surrogates (Fig. 10). These variables were chosen because they are commonly available variables surveyed in the regions. Furthermore, the future projections for these data are available in many regions (e.g., Chae, 2016).

Table 6 shows the association between the surrogates and the original indicator data. Cropland is highly correlated to several stressors in the categories of catchment disturbance, pollution and water resource development. Population shows high correlations with a few stress indicators, including impervious surfaces (S2) and human water stress (S17), which are highly correlated with major cities that have large populations. Fig. 10 shows that the water use level has a spatial distribution similar to the population except for the southwestern regions of Korea, where agricultural water use is relatively high.

These three surrogates are used to estimate the AT index with a linear regression, as shown in Fig. 11. Compared to the original index in Fig. 9a, the spatial distributions over Korea are quite similar but with some differences, as shown in Fig. 11b. The decent estimates suggest that it is possible to use a limited number of indicators to understand the future water sustainability of the region.

Table 6
Correlations between indicators and surrogates from the Korean datasets for a spatial resolution of R25 and the reference year of 2010.

	Driver	Cropland	Population	Water use
S1	Cropland	1.00	0.28	0.57
S2	Impervious surfaces	0.57	0.81	0.75
S3	Livestock density	0.77	0.48	0.67
S4	Wetland disconnectivity	0.63	0.11	0.28
S6	Nitrogen loading	0.66	0.38	0.38
S7	Phosphorus loading	0.68	0.39	0.40
S9	Pesticide loading	0.96	0.28	0.53
S10	Sediment loading	0.59	0.13	0.12
S11	Organic loading	0.66	0.40	0.38
S14	Dam density	0.65	0.39	0.56
S15	River fragmentation	0.16	0.37	0.28
S16	Consumptive water use	0.82	0.53	0.69
S17	Human water stress	0.55	0.78	0.69
S18	Agricultural water stress	0.95	0.31	0.55
S19	Flow disruption	0.34	0.29	0.36
S20	Non-native fishes (%)	0.22	0.25	0.30
S23	Aquaculture pressure	0.51	0.38	0.57
B1	Dam density	0.65	0.39	0.56
B2	Flow disruption	0.34	0.29	0.36
B3	Moderate water use	−0.30	−0.11	−0.21
B4	River corridor access	0.63	0.11	0.28
B5	Access to clean drinking water	0.08	0.58	0.46

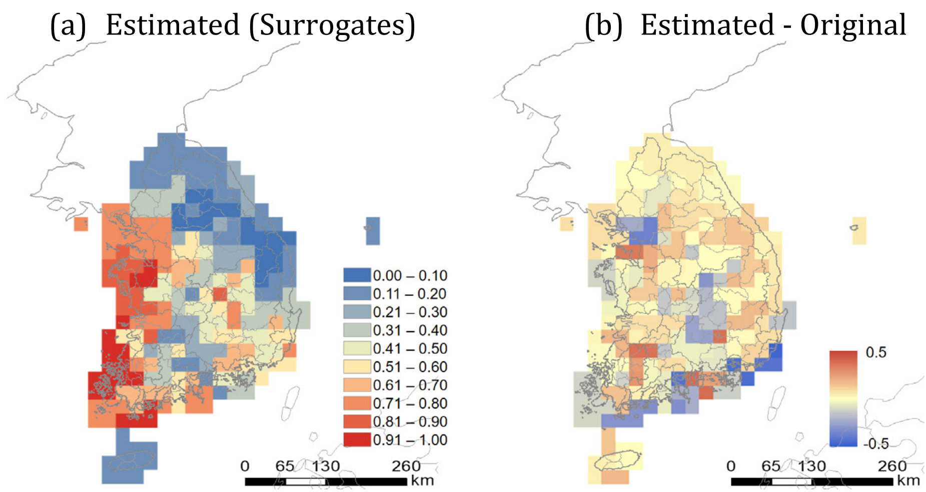

Fig. 11. (a) Adjusted threats with the three surrogate indicators of crop land, population and water use and (b) their difference from the original for the year 2010 at a spatial resolution of 0.25°.

6. Conclusions

In this study, we sought to understand the robustness of indicator-based studies in quantifying sustainable water use using the example of adjusted human water security from Vörösmarty et al. (2010). First, we showed strong correlations between the regional data and global data even though the regional-level investment benefit data do not correspond well to the global data for this element. We revealed that the global data, particularly those constructed from remotely sensed data, adequately capture the local variability of the regional data.

However, the global investment benefits do not fully capture the complexities of investments at the regional scale given better local information. Different patterns of threat occur when the analysis is performed at smaller spatial scales (0.25° and 0.10°), suggesting that regional analysis might be more appropriate for watershed planning and water resource development.

Finally, the spatial variation in incident threat could be adequately represented by a smaller number of variables. While our study focused on only the present-day index, the results suggest that it would be possible to predict water security or sustainability for future periods with a limited number of indicators. Since data such as land use and population are often projected for the future in many regions as part of socio-economic scenarios, further studies to predict worldwide water security will be feasible. In addition, relationships between the socio-economic indicators and water security could be developed differently for different regions and countries for global projection.

Furthermore, indicator-based studies are intended to provide the general spatial or temporal variations of water resource security threats, not specific local information. The estimated index provides guidance for developing strategic plans for water resource development. More detailed investigations should be followed for further planning.

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